IMPROVEMENT OF FUZZY NEURAL NETWORK USING MINE BLAST ALGORITHM FOR CLASSIFICATION OF MALAYSIAN SMALL MEDIUM ENTERPRISES BASED ON STRENGTH

KASHIF HUSSAIN TALPUR

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Universiti Tun Hussein Onn Malaysia

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ABSTRACT

Fuzzy Neural Networks (FNNs) with the integration of fuzzy logic, neural networks and optimization techniques have not only solved the issue of "black box" in Artificial Neural Networks (ANNs) but also have been effective in a wide variety of real-world applications. Despite of attracting researchers in recent years and outperforming other fuzzy inference systems, Adaptive Neuro-Fuzzy Inference System (ANFIS) still needs effective parameter training and rule-base optimization methods to perform efficiently when the number of inputs increase. Many researchers have trained ANFIS parameters using metaheuristic algorithms but very few have considered optimizing the ANFIS rule-base. Mine Blast Algorithm (MBA) which has been improved by Improved MBA (IMBA) can be further improved by modifying its exploitation phase. This research proposes Accelerated MBA (AMBA) to accelerate convergence of IMBA. The AMBA is then employed in proposed effective technique for optimizing ANFIS rule-base. The ANFIS optimized by AMBA is used employed to model classification of Malaysian small medium enterprises (SMEs) based on strength using non-financial factors. The performance of the proposed classification model is validated on SME dataset obtained from SME Corporation Malaysia, and also on real-world benchmark classification problems like Breast Cancer, Iris, and Glass. The performance of the ANFIS optimization by AMBA is compared with Genetic Algorithm (GA), Particle Swarm Optimization (PSO), MBA and Improved MBA (IMBA), respectively. The results show that the proposed method achieved better accuracy with optimized rule-set in less number of iterations.

ABSTRAK

Rangkaian Neural Kabur dengan integrasi Logik Kabur, Rangkaian Neural dan teknik pengoptimuman bukan sahaja menyelesaikan isu “Black Box” di dalam Kecerdasan Rangkaian Neural tetapi juga berkesan dalam pelbagai aplikasi dunia sebenar. Walaupun iany menarik penyelidik dalam tahun-tahun kebelakangan ini dan mengatasi sistem inferens kabur lain, Sistem *Inferens Adaptive Neuro-Fuzzy* (ANFIS) masih memerlukan parameter dan Peraturan dengan menggunakan kaedah pengoptimuman yang lebih berkesan apabila ada pentambahan input. Kebanyakan penyelidik telah melatih parameter bagi ANFIS dengan menggunakan algoritma metaheuristic, tetapi hanya sedikit sahaja yang dipertimbangkan untuk pengoptimuman ANFIS berasaskan-peraturan. Kajian ini mencadangkan teknik yang berkesan untuk mengoptimumkan ANFIS berasaskan peraturan dan melatih parameter rangkaian menggunakan kaedah baru yang dibangunkan iaitu Algoritma Mine Blast (MBA) selepas mengubah suai fasa eksploitasi untuk mempercepatkan kelajuan penumpuan, yang dikenali MBA pecutan (AMBA). AMBA teroptimum di dalam ANFIS telah dilaksanakan untuk memodelkan kekuatan bagi sistem ramalan Perusahaan Industri Kecil Sederhana (IKS) Malaysia menggunakan faktor bukan berasaskan kewangan. Prestasi bagi kekuatan model ramalan yang dicadangkan telah diujilari menggunakan set data yang diperolehi daripada SME Corporation Malaysia. Untuk pengesahan lanjut, AMBA teroptimum ANFIS juga telah diuji dengan menggunakan set data penanda aras bagi masalah klasifikasi seperti Kanser Payudara, Iris, dan Kaca. Prestasi model ANFIS AMBA teroptimum yang dicadangkan telah dibandingkan dengan Algoritma Generik (GA), Pengotimuman Kawanan Zarah (PSO), MBA dan MBA tambahbaik (IMBA) yang dioptimumkan setiap satu darinya. Keputusan menunjukkan bahawa AMBA teroptimum ANFIS yang dicadangkan mencapai ketepatan yang lebih baik dengan set peraturan yang optimum, iaitu dalam jumlah kurang daripada penilaian fungsi berbanding dengan

keputusan yang diperolehi daripada GA, PSO, MBA, dan IMBA teroptimum ANFIS, setiap satu darinya.

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LIST OF SYMBOLS AND ABBREVIATIONS

a	-	Reduction constant in MBA
A_i	-	ith fuzzy set of input variable A for ANFIS
B_i	-	ith fuzzy set of input variable B for ANFIS
c	-	Center parameter of Gaussian type membership function
c_1, c_2	-	Acceleration coefficients in PSO
$\cos(\theta)$	-	Represents calculation of direction of shrapnel pieces in MBA
d_{n+1}^f	-	Distance of shrapnel pieces in MBA
F_{n+1}^f	-	Function value of currently exploding landmine in MBA
F_n^f	-	Function value of best landmine in MBA
$4f_i$	-	Node function for ith rule
$f(x)$	-	Fitness function
σ	-	Width parameter of Gaussian type membership function
$\prod$	-	Product operator to calculate firing strength of ith rule in ANFIS
θ	-	Direction
k	-	Iteration number index of MBA
m_{n+1}^f	-	Direction of shrapnel pieces in MBA
N_d	-	Search dimension
N_{pop}	-	Population of MBA
N_s	-	Number of shrapnel pieces in an individual of population in MBA
$O_{1,i}$	-	Output of ith node in layer 1 of ANFIS

$O_{2,i}$	-	Output of *i*th node in layer 2 of ANFIS
$O_{3,i}$	-	Output of *i*th node in layer 3 of ANFIS
$O_{4,i}$	-	Output of *i*th node in layer 4 of ANFIS
$O_{5,i}$	-	Output of *i*th node in layer 5 of ANFIS
O_{avg}	-	Average of selected rules' output
O^t	-	Target output in training pair
O_m^t	-	Target output of *m*th training pair
O^r	-	Rule output
p_i	-	Consequent parameter of *i*th rule, Personal best location of particle in PSO
p_g	-	Global best location in PSO
q_i	-	Consequent parameter of *i*th rule
r_i	-	Consequent parameter of *i*th rule
$rand$	-	generates uniformly distributed random numbers between 0 and 1
$randn$	-	Normally distributed pseudorandom number
μ	-	Exploration factor
$\mu_{A_i}(x)$	-	*i*th membership function of input variable *A*
$\mu_{B_i}(x)$	-	*i*th membership function of input variable *B*
v_i	-	Velocity of *i*th particle in PSO
v_{max}	-	Maximum velocity in PSO
w_i	-	Firing strength of *i*th rule in ANFIS
$\overline{w}_i$	-	Normalized firing strength of *i*th rule in ANFIS
$w(k)$	-	Inertia weight in PSO
x_i	-	Position of particle in PSO
X_{Best}	-	Current best exploding landmine in IMBA
X_{best-1}	-	Previous best exploding landmine in IMBA
$X_{e(n+1)}^f$	-	Location of exploding landmine in MBA
X_{n+1}^f	-	Location of next landmine to be exploded in MBA
X_0^f	-	First shot point in MBA
X_n^f	-	Location of best landmine in MBA
X^*	-	Optimal point of landmine explosion in MBA

D	-	Euclidean distances between current best point solution and current point of explosion in IMBA.
LB	-	Lower bound
SE	-	Squared Error
UB	-	Upper bound
AMBA	-	Accelerated Mine Blast Algorithm
ANFIS	-	Adaptive Neuro-Fuzzy Inference System
AWPSO	-	Adaptive Weighted Particle Swarm Optimization
ACO	-	Ant Colony Optimization
ABC	-	Artificial Bee Colony
ANN	-	Artificial Neural Network
BP	-	Backpropagation
CBR	-	Case Based Reasoning
CSO	-	Cat Swarm Optimization
CRM	-	Customer Relationship Management
DE	-	Differential Equation
DEACS	-	Differential Evolution with Ant Colony Search
DTW	-	Dynamic Time Warping
EKF	-	Extended Kalman Filter
FA	-	Firefly Algorithm
FFRLS	-	Forgetting Factor Recursive Least Square
FIS	-	Fuzzy Inference System
FNN	-	Fuzzy Neural Network
GA	-	Genetic Algorithm
GD	-	Gradient Descent
IMBA	-	Improved Mine Blast Algorithm
IQPSO	-	Improved Quantum behaved Particle Swarm Optimization
ISO	-	International Organization for Standardization
LSE	-	Least Square Estimation
MRS	-	Manufacturing and Manufacturing Related Industries
MSE	-	Mean Squared Error

MF	-	Membership Function
MBA	-	Mine Blast Algorithm
NN	-	Neural Network
PSO	-	Particle Swarm Optimization
QPSO	-	Quantum behaved Particle Swarm Optimization
SVD	-	Singular Value Decomposition
SME	-	Small Medium Enterprises
SCORE	-	SME Competitiveness Rating For Enhancement
SE	-	Squared Error
SOP	-	Standard Operating Procesure
UCI	-	University of California Irvine
UCIMLR	-	University of California Irvine Machine Learning Repository
WT	-	Wavelet Transform

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LIST OF PUBLICATIONS

Journal Articles

(i) Kashif Hussain, Mohd. Najib Mohd. Salleh. "Optimization of Fuzzy Neural Network using APSO for Predicting Strength of Malaysian SMEs", Asian Journal of Control. (In Press)

(ii) Kashif Hussain, Mohd. Najib Mohd. Salleh, Abdul Mutalib Leman. "Optimization of ANFIS using Mine Blast Algorithm for Predicting Strength of Malaysian Small Medium Enterprises", Journal of Intelligent & Fuzzy Systems. (In Press)

(iii) Kashif Hussain, Mohd. Najib Mohd. Salleh. "Analysis of Techniques for ANFIS Rule-Base Minimization and Accuracy Maximization", ARPN Journal of Engineering and Applied Sciences. (In Press)

(iv) Khalid Hasnan, Aftab Ahmed, Badrul-Aisham, Qadir Bukhsh, Kashif Hussain. "A Novel Optimal RFID Network Planning by MC-GPSO", International Journal of Control and Automation. (In Press)

Conference Presentations

(i) 10th Asian Control Conference 2015 (ASCC'15). Kota Kinabalu, Sabah, Malaysia. 31st May – 3rd June 2015

(ii) The International Conference on Electrical and Electronic Engineering 2015 (IC3E'15). Melaka, Malaysia. 10-11 August 2015

(iii) 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD'15). Zhangjiajie, China. 15-17 August 2015

(iv) International Conference on Green Computing and Engineering Technology 2015 (ICGCET'15), Dubai, UAE. 25-26 July 2015

CHAPTER 1

INTRODUCTION

Artificial Neural Networks (ANNs) suffer from the difficulty of explaining their decisions (black box) which confines their applicability in practice. Fuzzy Neural Networks (FNNs) solve this by adding rules to neural networks but they lack effective learning capability. The adaptive nature of Adaptive Neuro-Fuzzy Inference System (ANFIS) has not only outperformed ANNs and other types of fuzzy expert systems, but also has proved its applicability in a wide variety of areas including business and finance. However, most of the applications of soft computing techniques including ANFIS have been proposed for large firms using financial information. But, in small business sector which contributes to employment generation, gross domestic product (GDP) and sustainable economic growth of a country has been ignored. In rapidly changing global business environment, Malaysian small and medium enterprises (SMEs) are facing new challenges and also the fear of failing has increased. Thus, forecasting the strength of an SME and its ability to repay over the period of loan have been major concerns of lending institutions.

1.1 Research Background

Recently introduced neural network (NN) models, with their learning capability, have outperformed the statistical models due to their excellent performance of treating non-structured and non-linear data (Chen, 2013). However, neural networks suffer from the difficulty to deal with imprecise information and the "black box" syndrome that more or less has limited their applications in practice (Fu-yuan, 2008). The "black box" refers to an issue of inability of NN to show how it made up to an output. Once a decision is made then it is very difficult to explain the reason behind it (Pradhan *et al.*, 2011). To overcome this drawback, NNs are integrated with fuzzy inference to form Fuzzy Neural Networks (FNNs). Such hybrid systems combining fuzzy logic, neural networks, optimization techniques, and expert systems are proving their effectiveness in a wide variety of real-world problems (Fuller, 1995).

Various optimization techniques/learning algorithms have been used with NNs to reduce the cost of learning. These algorithms search through solution space to find a function that has the smallest possible cost. Most of these algorithms are based on numerical linear and nonlinear programming methods that require substantial gradient information and usually seek to improve the solution in the neighborhood of a starting point. The gradient search may become difficult and unstable when the objective function and the constraints have multiple or sharp peaks. To improve learning capability of FNN, many researchers have optimized the training process by various metaheuristic algorithms like Genetic Algorithm (GA) which is based on the genetic process of biological organisms, and Particle Swarm Optimization (PSO) or Ant Colonies which are modeled on swarm intelligence (Liu *et al.*, 2013; Pousinho *et al.*, 2011). Recently, Sadollah *et al.* (2012) have introduced metaheuristic algorithm Mine Blast Algorithm (MBA) which has outperformed GA, PSO, and their variants in terms of convergence speed and better optimal solutions. The improved variant of MBA has been introduced by Sadollah *et al.* (2014). This research further accelerates its convergence speed by modifying exploitation phase and calling the new variant as Accelerated MBA (AMBA).

In recent years, Adaptive Neuro-Fuzzy Inference System (ANFIS) has gained more attraction than other types of Fuzzy Inference Systems (FIS), because the results obtained from it are equally robust as of the statistical methods. Moreover, it is easy to understand, flexible, tolerant to imprecise data and able to handle non-linear functions (Taylan *et al.*, 2009). The major problem with FNNs including ANFIS is the number of rules which increase exponentially as the number of inputs increase. Thus, the more number of rules, the more is the complexity of ANFIS architecture and its computational cost. But, it is also noteworthy that over reducing the number of rules results in the loss of accuracy (Rini *et al.*, 2014). To overcome the issue, this research proposes optimization technique for reducing fuzzy rule-base in ANFIS architecture and effective ANFIS parameter training using AMBA. It reduces fuzzy rules in ANFIS structure to obtain optimized rule-set so that acceptable accuracy could be achieved.

Many statistical and artificial intelligence (AI) techniques (Bakar *et al.*, 2012; Liu *et al.*, 2010; Pederzoli *et al.*, 2010; Zhou *et al.*, 2010) have been proposed for finding strength of a business in the form of bankruptcy/default/distress prediction and credit risk assessment, like Altman Z-Score, linear regression, logistic regression, classification trees, logit model, ANN, FNN, but mostly they have trended towards financial statements or financial ratios. These financial factors have been useful for determining financial crisis of a large firm. However, SMEs have their special features which make them distinct from larger ones in operating style, firm structure and decision making procedure (Wang *et al.*, 2011). Moreover, unlike larger firms, they are not equipped with dedicated resources to manage risks therefore they sometimes fail to ensure sustainability (Clusel *et al.*, 2013). These small firms are very centered on the entrepreneurs and their skills in areas like management, marketing and production etc. These non-financial factors, in globally challenging environment, play more important role for the success of an SME (Zulkifli-Muhammad *et al.*, 2009).

SME Corporation Malaysia has identified the most important non-financial factors associated with the performance of an SME. These factors which vary across sectors are used as inputs to their own developed star ranking system called SCORE (SME Competitiveness Rating for Enhancement). SCORE is a software diagnostic tool which assigns star rating to indicate performance level of SMEs that are registered with SME Corporation Malaysia (Malaysia, 2014). Utilizing these non-financial factors, the proposed ANFIS optimization technique has been employed to model classification of Malaysian SMEs based on strength. The proposed classification model takes following 7 non-financial factors as its inputs and produces 1 output which depicts the class of an SME based on its strength. For example, an SME can have either "low production capability" or "high production capability". The aforementioned 7 non-financial factors are related to manufacturing and manufacturing related services (MRS) which are explained below:

i. Business Performance

There are different indicators which gage performance of a business. These include revenue, marketing, and client satisfaction. The sales revenue is further divided into revenue of the current year, average percentage of growth in last 3 years' revenue, average percentage of the export services derived from the last 3 years. The other component of gaging business performance is marketing which is observed in terms of medium of marketing used and amount served for this purpose. The third and last area of evaluating business performance is customer satisfaction which is further evaluated by answering 3 questions. These questions are related to importance of the customer feedback, how feedback is utilized to improve business, and whether or not the SME has dedicated staff for Client Relationship Management (CRM).

ii. Financial Capability

Lending organizations always look for great financial capabilities of SMEs in order to smoothly receive repayments. SME's financial capability imitates ability to manage day-to-day financial operations. The financial capability of an SME is assessed by the value of 7 head in the financial statements for the current year. These variables include the amount of current assets, current liabilities, stakeholder equity, total assets, gross profit, net profit, and retained earnings.

iii. Technical Capability

SME's technical capabilities are firmly founded on a competent, capable and talented team of professionals. Technically strong SMEs are more capable of generating sales because they are equipped with technical resources which include men, machines, processes and materials that are used in the industry. There are 3 different sub-factors which are considered in this area. These include percentage of both technical and management staff, number of qualified staff (both technical and management), and type of process technology utilized.

iv. Production Capability

Production capability defines how efficiently an SME, using the input and available resources, is producing maximum output. It has the ability, expertise, and efficient working environment to meet customers demand within limited time period. To measure the capability of production of an SME, 5 sub-areas are gaged. They are capital investment per employee, level of automation, utilization of machine/software/equipment in overall production process, production rate, and rejection rate of products.

v. Innovation

Doing the same business in the same old way and expecting different results is not going to work for any business today. In globally challenging business environment, innovation in SMEs means doing business with creativity and diversity; i.e. by making use of social media, internet business and website etc.

vi. Quality System

Quality is not just about reliability of product or service that is offered by a business, but it involves quality checks in each step from production process to delivery to customer. Here, the standard operation procedures (SOPs) of various activities, at different levels, performed in SME are evaluated. The quality system certifications (i.e. ISO, Halal etc.) and other awards, if achieved by the SME, are also verified.

vii. Management Capability

Unlike larger firms, SMEs fail due to incapable owner-managers. Management capability leads an SME to sustainable growth and survival in difficult times. This variable of SCORE system gages high-level strategic and management functions in a company. The vision and mission statements, company organogram, employee training and appraisal system are sought. In addition, strategy for encouraging innovation and use of information technology is also assessed.

1.2 Problem Statement

SMEs are integral part of Malaysian economic growth. Malaysian SMEs contribute not only to domestic economic sustainability but also to export demands significantly. Thus, the government organizations need to identify the needy SMEs for their support by classifying SMEs based on their strength. On the other hand, before extending a loan, financing institutions need to determine the strength of a potential counterparty in order to expect smooth repayments and reduce non-performing loans. In case of SMEs, non-financial factors play more important role as they mostly rely on skills and capabilities of entrepreneurs.

Adaptive Neuro-Fuzzy Inference System (ANFIS) which is a form of Fuzzy Neural Network (FNN) has outperformed Neural networks (NNs) and other types of Fuzzy Inference Systems (FIS) in terms of accuracy. ANFIS discourages large number of inputs due to exponential increase in rules. Many researchers have trained

ANFIS network using metaheuristic algorithms but very few have considered optimizing its rule-base. Thus, there is a need of effective training and rule-base optimization technique for ANFIS which may help reduce its computational time.

So far, many optimization and learning algorithms have been developed, hybridized, and improved by modifying one or the other parameters they accept; like in case of Improved GA, Hybrid GA, and Quantum Behaved PSO etc. An efficient evolutionary algorithm should take less processing time and achieve higher accuracy. A newly developed Mine Blast Algorithm (MBA), when compared with several well-known metaheuristic algorithms (i.e. GA, PSO, DE etc.) while solving unconstrained and constrained engineering problems, has shown faster convergence and better optimal solutions. MBA is improved by Improved MBA (IMBA) but it can be further improved by modifying its exploitation phase. To accelerate convergence of IMBA, the previous best solution can be replaced by the current available solution.

This research proposes an effective technique for training ANFIS parameters and optimizing its rule-base. This technique is then integrated with Mine Blast Algorithm after improving its convergence. The optimized ANFIS is then employed to classify Malaysian SMEs based on their strength.

1.3 Aims of Study

The aim of this research project is to accelerate the convergence speed of Mine Blast Algorithm (MBA) by modifying its exploitation phase; calling it Accelerated MBA (AMBA). This research also aims at reducing fuzzy rule-base of ANFIS architecture by proposing optimization technique to achieve optimized rule-set with better accuracy. For effective training and optimization of ANFIS network, AMBA is used. This optimized ANFIS network is employed to model classification of Malaysian SMEs based on strength using non-financial factors as its inputs.

1.4 Objective of Study

This study embarks on the following objectives:

(i) To accelerate the convergence speed of Mine Blast Algorithm (MBA) by modifying its exploitation phase; calling it Accelerated MBA (AMBA);

(ii) To apply AMBA to optimize fuzzy rule-base in Adaptive Neuro-Fuzzy Inference System (ANFIS) architecture and effectively train ANFIS parameters to achieve better accuracy for modeling classification of Malaysian SMEs based on strength.

(iii) To evaluate Objective II, compare the results with the ANFIS optimized by Genetic Algorithm (GA), Particle Swarm Optimization (PSO), MBA and Improved MBA (IMBA), respectively, in terms of optimized rule-set, accuracy, and number of iterations.

1.5 Scope of Study

This research was focused on the following solutions to the problem:

- Classifying Malaysian SMEs based on strength. Only the small and medium sized firms that come under the definition provided by SME Corporation Malaysia (see Appendix B for SME definition) were part of this research. The firms that did not fulfill the definition were not considered in this research.
- The SME classification model used 7 non-financial factors as inputs and each input is limited to two membership functions: "Low" and "High".
- Optimization of ANFIS, using AMBA, to classify Malaysian SMEs based on strength.
- The performance of the proposed method was compared with the ANFIS networks optimized by Genetic Algorithm (GA), Particle Swarm Optimization (PSO), MBA and Improved MBA (IMBA), respectively. The results were compared and analyzed in terms of optimized rule-set, accuracy, and number of iterations.

1.6 Significance of Study

The research discovered effective learning ability of ANFIS; used for classification of Malaysian SMEs based on strength. The results of AMBA showed faster convergence rate, better optimized solutions with less number of iterations.

SME Corporation Malaysia and other lending organizations will be able to forecast firm's ability to repay over the life of the loan. The management of SMEs will know the problems they are about to face and, where appropriate, take corrective actions.

1.7 Project Schedule

This project was carried out in one and a half year. The summary of activities during the research process has been stated in APPENDIX A.

1.8 Outline of the Thesis

This thesis comprises of five chapters including Introduction and Conclusion chapters. The followings are synopsis of each chapter.

Chapter 1: *Introduction*. Apart from providing an outline of the thesis, this chapter contains an overview of the research background, problem to be solved, objectives to achieve, scope, aim, and significance of the study.

Chapter 2: *Literature Review.* This chapter reviews some of the work on soft-computing techniques that has already been applied by researchers while solving problems related to finance and economics. After reviewing existing research, fundamental theory of fuzzy neural network and ANFIS along with their architecture, learning mechanism and applications has been presented. This is followed by introducing the targeted optimization algorithm for ANFIS learning that is MBA. Its improved version that already exists has also been presented in the end of this chapter. This chapter lays the foundation for introducing the proposed method for ANFIS optimization and its efficient learning through modified MBA – as described in Chapter 3.

Chapter 3: *Research Methodology***.** This chapter discusses the research methodology used to carry out the study systematically. First, existing work on ANFIS training and optimization has been analyzed and compared. The difference between optimization algorithms is stated later on in this chapter. The proposed modification in MBA and ANFIS optimization has been illustrated. In the end of this chapter, the performance validation methods for the proposed methodology has been explained.

Chapter 4: *Results and Analysis.* The new rule-base optimization algorithm for ANFIS, in integration the proposed AMBA, is further validated for its efficiency and accuracy on industry and benchmark problems. The performance of the proposed algorithm was tested in comparison with GA, PSO, and standard MBA and its variant IMBA. The performance evaluation was carried out based on optimized rule-set, accuracy, and number of iterations to converge.

Chapter 5: *Conclusion and Future Works.* The contributions of the proposed ANFIS optimization technique are summarized, and the recommendations are given for further continuation of work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Fuzzy Neural Networks (FNNs) have been widely applied in business and economics like supply chain management, stock market, price prediction, gas condensate, energy consumption, electric load forecasting etc. (Kar *et al.*, 2014). Practically, there exist three types of fuzzy systems: pure fuzzy systems, Mamdani type and Sugeno type fuzzy inference systems (Liu *et al.*, 2004). But, the most commonly used is Sugeno model since it is computationally less expensive and more transparent than other counterpart models (Awadallah *et al.*, 2009). Adaptive Neuro-Fuzzy Inference System (ANFIS) is the first order Sugeno-type FNN which uses derivative based learning which has high probability of falling in local minima. The derivative-free techniques using metaheuristic algorithms are more powerful for ANFIS learning (Shoorehdeli *et al.*, 2009). Thus, this research improves the newly developed metaheuristic algorithm Mine Blast Algorithm (MBA) by modifying its exploitation phase. The modified MBA is then used for training parameters of ANFIS and optimizing its rule-set.

The application of FNNs and ANFIS in business and economics have been reviewed in the following section. Section 2.3 compared different ANFIS training and optimization methods proposed by researchers. Metaheuristic algorithms have been analyzed in Section 2.4. Section 2.5 explains how FNNs work, followed by the discussion on ANFIS structure and its learning mechanism in the Section 2.6. Mine

Blast Algorithm (MBA) and its variant Improved MBA (IMBA) are presented in the Sections 2.7 and 2.8, respectively. The chapter is summarized in Section 2.9.

2.2 Applications of ANN, FNN, and ANFIS in Business and Economics

Many have contributed to research in the financial areas such as predicting financial crisis, bankruptcy and credit risk. Additionally, soft computing techniques have also been employed for currency, stock, and gold price forecast. But, no significant research is found on modeling small and medium enterprises (SMEs) strength/failure/distress or credit rating prediction using fuzzy neural networks – ANFIS specifically. Artificial Neural Networks (ANNs) have been widely used in business and finance because they have outperformed traditional statistical models in terms of accuracy (Chen, 2013). FNN, particularly ANFIS, has not only solved the "Black Box" issue of ANN but also achieved more accuracy than ANN models (Fang, 2012; Huang, 2008; Rui, 2010). Moreover, ANFIS models have gained more popularity than FNNs due to the advantage of computationally efficient, well-adaptable with optimization and adaptive techniques (Neshat *et al.*, 2011; Petković *et al.*, 2014).

Pradhan *et al.* (2011) proposed ANN based financial viability prediction model using Z-score financial ratios. In their research, the authors stated that it is extremely difficult to rational ANN decision because of "Black Box" whereas, FNNs solve it through rules. Siraj *et al.* (2011) proposed loan decision support system for Malaysian SME banks and financial institutions using a hybrid of ANN and Case Based Reasoning (CBR). Their system could recommend management to accept or reject a loan application. They developed their model based on SME expert criteria collected from corporate sector and financial institutions such as SME banks and SME Corporation Malaysia. Liu *et al.* (2010) also employed ANN with Particle Swarm Optimization (PSO) to present credit evaluation model for Chines SMEs by adding non-financial indicators with financial ones. The proposed model outperformed ANN which learns through Back Propagation algorithm which is based on gradient descent. According to the author, PSO shortened training time by avoiding derivative process unlike back-propagation neural network, and achieved better accuracy.

Rui (2010) used FNN trained by improved PSO to present bankruptcy prediction and risk evaluation model for corporate firms listed in China stock market. The presented model utilized financial ratios. The results obtained indicate that the predictive accuracies of improved PSO trained FNN are much higher than the one trained by standard PSO. The research concluded that both ANN and PSO more or less suffer from slow convergence and also involve in local optimum solution.

Recently, Bagheri *et al.* (2014) proposed a hybrid artificial intelligence technique for foreign exchange trading advice. They implemented a hybrid of ANFIS, Quantum behaved PSO (QPSO), Dynamic Time Warping (DTW), and Wavelet Transform (WT). In this research, QPSO was used to tune membership functions of ANFIS while WT method was employed for automatic extraction of patterns from a financial time series. Instead of just predicting the price of stock, the proposed model could help traders by making correct trading signals based on both chart patterns and past exchange rate values. Chen (2013) also used PSO for ANFIS structure learning through subtractive clustering. He presented a model for predicting business failure, using 13 financial ratios, targeting electronics companies listed on Taiwan Stock Exchange Corporation. Chen found that neural network models are not suitable for adaptive learning because they face the issues of choosing optimal initial structure, inability to arriving at local minimum, and incapability of explaining their decisions. The same year, Nhu *et al.* (2013) trained ANFIS parameters by Firefly Algorithm (FA) to propose stock price prediction model for Vietnam Stock Market. They stated in their research that obtaining optimum parameters of ANFIS is the main problem in its implementation. Their proposed ANFIS with FA outdid the performance of models trained by PSO, back-propagation and the standard Hybrid learning in Matlab Tool Box. For the forecast of financial crisis, Fang (2012) proposed ANFIS based model which performed better than ANN. Like other authors mentioned above, Fang also focused corporate firms as well as financial information as input to the proposed model.

Taking a decade's period of 2002 to 2012, Kar *et al.* (2014) reviewed applications of FNNs including ANFIS models in the field of finance and economics, and nine other categories. They found that ANFIS was used in most of the articles related to forecasting and predictions category. It was also observed that ANFIS is less complex and easy to understand therefore it has been widely accepted in fuzzy inference systems. The authors found that adjusting weights of fuzzy inference systems is quite tedious job. Thus, they suggested putting more emphasis on the training algorithms to properly select optimum parameters. For future work, the authors foresee more innovation in ANFIS learning mechanisms as well as huge scope of ANFIS applications in economics.

For optimizing fuzzy rule-base in ANFIS architecture, Rini *et al.* (2014) integrated PSO with ANFIS. They reduced the number of rules by placing threshold value on rule's firing strength. The research found acceptable accuracy with optimal number of rules while testing their proposed approach on six benchmark classification problems. On the other hand, Gorzalczany (2001) also suggests in his book *"Computational intelligence systems and applications: neuro-fuzzy and fuzzy neural synergisms"* that pruning weaker rules from the fuzzy rule-base of ANFIS improves interoperability of the system.

As Shoorehdeli *et al.* (2009) suggest that metaheuristic algorithms are more useful than derivative based training of ANFIS architecture, so MBA can be applied for ANFIS training and optimization. MBA was introduced by Sadollah *et al.* (2012) which outperformed GA, PSO and their variants in terms of convergence speed and optimal solutions while solving several truss structure optimization problems. The improved version of MBA, namely Improved MBA (IMBA), was also proposed by Sadollah *et al.* (2014). This time, they replaced the aspect of direction by distance between the current best solution and the previous one; in exploitation phase of MBA. Even though, MBA was improved by modifying its exploitation phase, it can still be improved by focusing just on the distance between current best exploding point and the point of current explosion.

A review of literature in this section and a comparative analysis in Section 2.3 show three major gaps to be filled in research: (1) Despite of outperforming other metaheuristic algorithm, in terms of convergence speed and optimal solutions, MBA can still be improved by modifying its exploitation phase; (2) Effective training and optimization methods of ANFIS architecture are still required in order to achieve more accuracy with optimum rule-set in less computational cost; (3) Most of the research, related to business and finance with applicability of FNNs and ANFIS, has been trended towards large firms and financial information – ignoring SMEs and their important non-financial factors.

To address these gaps, this research proposed a variant of MBA, the so called Accelerated MBA (AMBA), which modified exploitation phase of IMBA and focused on the distance between current best exploding point and the point of current explosion, instead of considering both the current best and previous best points of explosion. This way it further improved the speed of convergence. For optimizing ANFIS rule-base and effectively training its parameters, this research proposed a modified two-pass learning algorithm for ANFIS using AMBA. The ANFIS optimized by AMBA was then employed to model classification of Malaysian SMEs based on strength using non-financial factors as inputs.

2.3 Comparative Study of ANFIS

Significant research has been carried and various hybrid methods have been developed by researchers for optimizing ANFIS structure and training its parameters. Structure learning and parameters identification are the two dimensions of ANFIS training. Some have focused on either of the two dimensions while some have tried to work on both of the issues. But, keeping balance between reducing the complexity of the ANFIS structure and increasing its accuracy by parameter tuning is often a challenge.

The original ANFIS proposed by Jang (1993) uses hybrid learning mechanism; a combination of gradient descent (GD) for tuning antecedent parameters and least square estimation (LSE) for consequent parameters identification. But, the drawbacks of GD, including complexity and tendency to trap in local minima, have opted the researchers to different alternatives. These alternatives comprise of metaheuristic optimization algorithms. The basic idea behind these population based optimization algorithms is to create a population of solution candidates. These solution candidates iteratively explore the search space and exchange information, thus chances of converging on the global minima are significantly increased.

Extensive literature review shows that a variety of metaheuristic algorithms have been integrated with ANFIS, such as PSO, GA, ABC, and their variants, for a range of problems of prediction, classification and control. These optimizers have either been used in combination with other ones or alone for parameter identification of antecedent and consequent parts of ANFIS. Mostly, PSO and its variants have been applied on ANFIS training and optimization.

As literature shows, (Catalao *et al.*, 2011; Jiang *et al.*, 2012; Pousinho *et al.*, 2011, 2012) have used PSO in combination with LSE to train antecedent and consequent parameters of their ANFIS models, respectively. They just focused on parameter learning, did not optimize fuzzy rule-set in their ANFIS architecture. They developed their ANFIS based prediction models for predicting electricity prices, wind power and customer satisfaction for a new product. Turki *et al.* (2012) and Rini *et al.* (2013) applied PSO alone for training both the premise and consequent parameters of their ANFIS based models. Rini *et al.* (2013) also used PSO for ANFIS training. In addition to parameter identification, they also optimized fuzzy rule-base by applying threshold value on the rules' firing strength.

Other than standard PSO, variants of this optimizer have also been employed to ANFIS learning. Bagheri *et al.* (2014) proposed Foreign Exchange Market trend forecasting system using ANFIS tuned by Quantum-behaved PSO (QPSO). Whereas, Liu *et al.* (2013) improved QPSO for tuning membership functions (MFs) of ANFIS, and identified consequent parameters by LSE. Another variant Adaptive Weighted PSO (AWPSO) with, one of least square methods, Forgetting Factor Recursive Least Square (FFRLS) was proposed by Shoorehdeli *et al.* (2009) for identification of premise and consequent parameters, respectively. The same authors Shoorehdeli *et al.* (2009) improved their previous research by employing Extended Kalman Filter (EKF), another form of least square methods, with AWPSO.

Other than PSO, as empirical study suggests, GA is the second most common approach to ANFIS identification. Soleimani *et al.* (2012) deployed GA and Singular Value Decomposition (SVD) for the optimum design of both Gaussian MFs and linear coefficients of the network, respectively. GA in combination with least square methods is implemented by Soto *et al.* (2014) and Malleswaran *et al.* (2011) to acquire optimum ANFIS network. The prior research used ANFIS for solving classification problem while the later one chose ANFIS to predict the values of Longitude and Altitude. Cardenas *et al.* (2011) trained all the parameters of ANFIS using GA alone for energy load forecast.

In the search of more effective training and optimization of ANFIS models, the researchers have explored the use of Artificial Bee Colony (ABC), Firefly Algorithm (FA), and Differential Evolution with Ant Colony Search (DEACS) algorithms (Karaboga *et al.*, 2013; Nhu *et al.*, 2013; Wang *et al.*, 2012). All of them were employed for both antecedent and consequent parameters learning. Wang *et al.*

(2012) were among others who, together with parameter identification, also optimized the rule-base by pruning redundant rules through threshold value on rules' firing strength. Cat Swarm Optimization (CSO) algorithm has also been proposed by Orouskhani *et al.* (2013) in conjunction with GD to train MFs and linear coefficients, respectively. Table 2.1 lists ANFIS training and optimization approaches discussed above.

Table 2.1: ANFIS optimization and training approaches

Research	ANFIS Training		ANFIS rule-base optimized
	MF	Consequent	
Pousinho *et al.* (2011)	PSO	LSE	No
Catalao *et al.* (2011)	PSO	LSE	No
Pousinho *et al.* (2012)	PSO	LSE	No
Jiang *et al.* (2012)	PSO	LSE	No
Sargolzaei *et al.* (2011)	PSO	PSO	No
Turki *et al.* (2012)	PSO	PSO	No
Rini *et al.* (2013)	PSO	PSO	Yes
Liu *et al.* (2013)	IQPSO	LSE	No
Bagheri *et al.* (2014)	QPSO	LSE	No
Shoorehdeli *et al.* (2009)	AWPSO	FFRLS	No
Shoorehdeli *et al.* (2009)	AWPSO	EKF	No
Soto *et al.* (2014)	GA	LSE	No
Malleswaran *et al.* (2011)	GA	LMS	No
Cardenas *et al.* (2011)	GA	GA	No
Karaboga *et al.* (2013)	ABC	ABC	No
Nhu *et al.* (2013)	FA	FA	No
Wang *et al.* (2012)	DEACS	DEACS	Yes
Orouskhani *et al.* (2013)	CSO	GD	No

The number of inputs in the models mentioned above had minimum two and maximum five inputs. Whereas, minimum MFs for each input were two and maximum six. Mostly, Gaussian shape of MFs was defined and, in addition to it, Triangular and Generalized Bell shape membership functions were also tried. The reason for common use of Gaussian shape was due to its number of parameters – only two (center and width). Due to less number of inputs, mostly researchers preferred grid partitioning method of input space partitioning. But, the wider usage of grid partitioning has been blocked due to curse of dimensionality. This means the number of rules and their linear coefficients increase as the number of inputs and MFs increase. This raises the need of optimizing the rule-base when using grid partitioning method. There is a little evidence of this matter as only Rini *et al.* (2013)

and Wang *et al.* (2012) are among other researchers, mentioned in Table 2.1, have tried obtaining useful rule-set by pruning less-important rules. They tried to perform accuracy maximization and complexity minimization simultaneously in order to achieve ANFIS systems with acceptable accuracy and high interpretability. But, Rini *et al.* (2014) also observed that optimizing the network with respect to one criterion, may poorly satisfy the other. Thus, choosing the right optimization method and training algorithm is crucial to efficient design of ANFIS network.

For the purpose of reducing complexity or, in other words, reducing the number rules, this research proposed optimization technique for obtaining optimum rule-set. To efficiently optimize and train ANFIS network, a newly developed optimization algorithm Mine Blast Algorithm (MBA) was employed for the first time with ANFIS. Before doing this, the research first modified MBA, calling it Accelerated MBA (AMBA), to improve its efficiency of finding optimum solution in less number of iterations. According to the scope of this study, performance of AMBA was compared with GA, PSO, and original MBA and IMBA; in integration with ANFIS. To better explore the possibility of improvement in these optimizers, below is the differences highlighted.

2.4 Difference between GA, PSO, MBA and IMBA

Nature-inspired optimization algorithms have become increasingly popular in recent years. Even though, they are widely accepted, it does not mean that we keep developing new algorithms of such kind. This will only lead to distraction from finding solutions of genuine challenges and problems in optimization. Instead, there is an immense need of digging in into the nature of these algorithms and solve key problems to make them more efficient (Yang, 2010).

This study presents insight into evolutionary algorithms; GA, PSO, MBA and IMBA, to make qualitative comparison based on two aspects of metaheuristic algorithms: exploration and exploitation. This way, we can improve one or the other area in these algorithms to find more efficient solutions in less number of iterations.

2.4.1 Three Steps of Population-based Algorithms

There are three steps each population-based algorithm goes through: initializing population, evaluating fitness of the individuals in a population, generating new population. These steps are performed until any of the two stopping criteria have reached: optimal or acceptable solution found or maximum number of generations produced as shown in Figure 2.1.

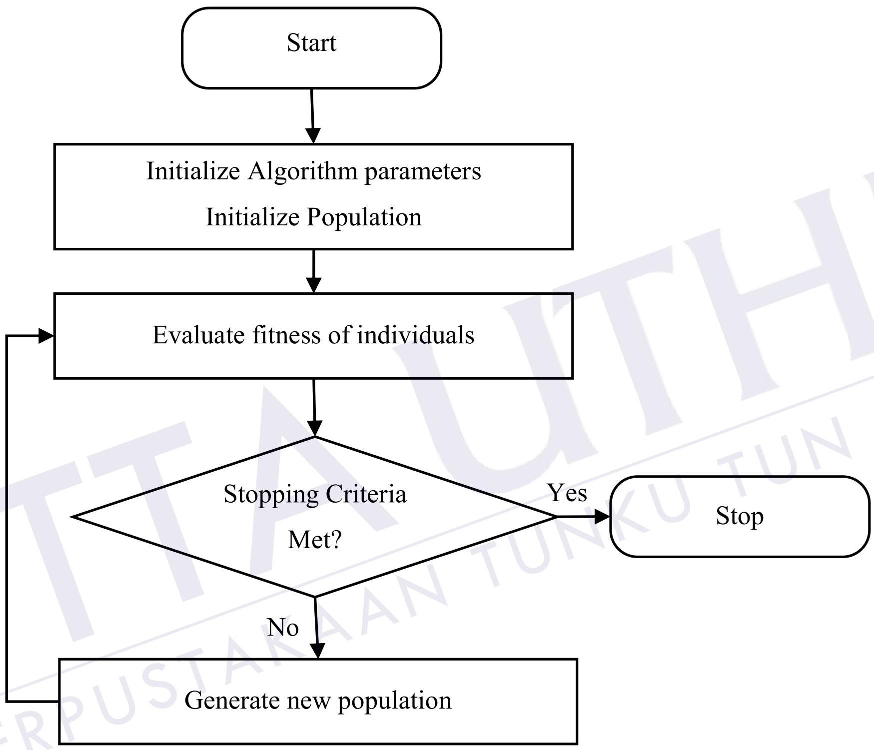

Figure 2.1: Flow of population-based algorithms

2.4.1.1 Initialize Population and Algorithm Parameters

All specified algorithms initialize their parameters and population in this step i.e. population size, maximum number of iterations and other performance related parameters. These parameters are influential to solution quality and cost in term of computational time. Poor choice of these parameters may result in low convergence, getting stuck to local minima and undesirable solutions (Sadollah *et al.*, 2014). Since, new population initialization may produce infeasible candidate solutions, it is important to choose right population representation. This is common for all optimization algorithms (Kachitvichyanukul, 2012).

GA, PSO, and MBA produce chromosomes, particles and shrapnel pieces as population individuals, respectively. GA calls it generation of chromosomes, PSO terms it as swarm of particles, while MBA refers to landmines in a minefield. MBA starts with an initial point(s) called first shot point(s) and generates initial population with first shot point(s). The choice of first shot point(s) may lead the search to different locations. MBA sets its initial parameters like reduction factor (α), exploration factor (μ), and maximum number of iterations (for detail refer to Section 2.7). All these algorithms initialize their population with random values.

2.4.1.2 Evaluate Fitness of Population Individuals

After a population is available, the main task is to find the optimal solution among solution candidates. The fitness function, which evaluates individuals, is defined by the user. It gives score to each individual based on how well it performed on a given task i.e. the value of difference between actual and desired output. Optimization algorithms select the individual from a population based on score it holds – potential solution. GA evaluates fitness of chromosomes and ranks them accordingly. PSO assesses the swarm of particles and records the historical best location of each particle, referred to as personal best location. PSO also updates overall best location thus far in the swarm, called global best location. The goal of MBA, in this process, is to explode the mines and find the most explosive mine with shrapnel pieces causing most casualties.

2.4.1.3 Generate New Population

Generating new population, after evaluation of the old one, is considered to be very crucial to producing feasible solution candidates relatively quickly; "early convergence". Each algorithm has its own operators or parameters to apply exploration and exploitation. Individuals in this step undergo a number of variation operations to roam around optimum area in search space.

In GA, after fitness evaluation, some individuals go through stochastic transformation by means of genetic operations (selection, crossover and mutation) to form new individuals. There are many crossover and mutation methods which are chosen in accordance to the problem being solved. In selection, two best chromosomes or solutions are selected and then the operation of crossover is performed to generate new chromosomes or generation. This new generation is injected some diversity by mutation function.

Just like GA, PSO also generates new population based on the optimum solutions found so far. Two key operations of PSO are the update of velocity and update of the position of particles. The velocity is updated with respect to inertia weight, experience of the particle and experience of the whole swarm as follows:

$$v_i(k+1) = w(k)v_j(k) + c_1 rand_1\big(p_i - x_i(k)\big) + c_2 rand_2(p_g - x_i(k)) \tag{2.1}$$

where v_i is ith velocity element in the vector v in iteration k. $w(k)$ is inertia weight, $rand_i$ and $rand_2 \sim U(0,1)$ are random variables, whereas $c_1 > 0$ and $c_2 > 0$ are acceleration coefficients influencing particle's personal best location p_i and global best location p_g, respectively. Then particles move to new location $x_i(k+1)$ as follows:

$$x_i(k+1) = x_i(k) + v_i(k+1) \tag{2.2}$$

where $x_i(k)$ is the current position of the ith particle.

Unlike GA, PSO does not require ranking of particles based on their fitness values. Thus, saving computing cost over GA. Also, update of velocity and position for generating new swarm does not need multiple operations, as in case of GA. This is done by simple arithmetic equations.

MBA and IMBA generate new population of shrapnel pieces by exploding landmine at location by equation Eq. 2.11. The detailed explanation of MBA and IMBA is given in sections 2.7 and 2.8, respectively.

2.4.2 Decision Parameters of Population-based Algorithms

Table 2.2 lists parameters which need to be predefined by the user. These parameters influence the performance of below mentioned metaheuristic algorithms in finding optimum solutions with efficient convergence.

Table 2.2: Decision parameters of GA, PSO, MBA, and IMBA

GA	
Population size (N_p)	Number of chromosomes in each generation
Maximum generations	Maximum number of iterations of producing a new generation
Selection	How to select parents for next generation. Options of selection are: Stochastic, Remainder, Uniform, Roulette, and Tournament.
Crossover	How to combine two individuals for reproduction: Single-point, Two-point, Uniform.
Mutation	Introducing new individuals by altering existing ones by Uniform and Gaussian types of mutation.
PSO	
Cognitive and Social Parameters (c_1, c_2)	Acceleration coefficients
Random ($rand_1, rand_2$)	Introducing diversity in search around optimum area.
Inertia Weight (w)	Controlling exploration and exploitation ability of a swarm.
Maximum Velocity (v_{max})	If the velocity value exceeds v_{max}, it gets reset to v_{max} accordingly.
MBA and IMBA	
Refer to Table 2.4	

2.5 Fuzzy Neural Network – FNN

Neural networks are good at recognizing patterns, but are not good at explaining how they reach their decisions. Fuzzy logic systems, which can reason with imprecise information, are good at explaining their decisions but they cannot automatically acquire the rules they use to make those decisions. Therefore, both are combined to form Fuzzy Neural Network (FNN) to overcome the difficulties and limitations of each other (Alhanafy *et al.*, 2010).

The major concerns while designing an FNN could be fuzzification of inputs, output, learning mechanism, and error function. It consists of fuzzy neurons capable of learning. These neurons performs common operations of fuzzy set theory inside inference engine to generate IF-THEN fuzzy rules. These rules provide mechanism of human-like reasoning. (Castellano *et al.*, 2007). An expert defines linguistic terms in the form of membership functions to express inputs in a human manner. These terms are used to define fuzzy rules consisting of two parts: antecedent – the condition part, and consequent – rule's result art. The output of FNN is the logical sum of all the rules obtained by defuzzifying the results' output (Issac *et al.*, 2014).

A simple example of FNN is illustrated by Figure 2.2. It is a three-layer architecture where first layer contains input variable, second layer holds fuzzy rules, while third layer represents output variables.

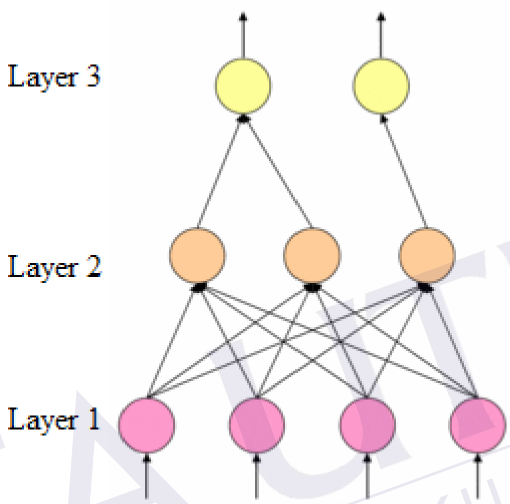

Figure 2.2: Layered Architecture of FNN (Kruse, 2008)

2.6 Adaptive Neuro-Fuzzy Inference Systems – ANFIS

Due to its adaptability, flexibility and ease in understanding, ANFIS has become attractive research topic in fuzzy systems (Kar *et al.*, 2014; Liu *et al.*, 2013). Since, it can be interpreted as local linearization modeling and conventional linear techniques for estimation and control, it has vast applicability (Kothandaraman *et al.*, 2012). Below presented is the theory of ANFIS structure, and how it learns its parameters is also explained.

2.6.1 ANFIS Structure

Jang (1993) introduced ANFIS architecture, a universal approximator based on adaptive technique to assist learning and adaptation, has been attractive research area in recent years (Ananda *et al.*, 2011). A number of researchers have developed neuro-fuzzy systems based on motivation to predict and solve economic crisis of various fields (Kar *et al.*, 2014).

The ANFIS model gets input as crisp numerical values and also generates crisp values in output with the help of following features illustrated in Figure 2.3:

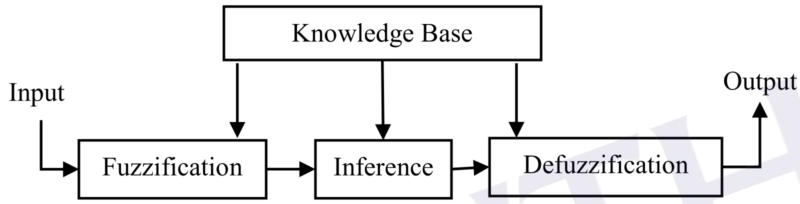

Figure 2.3: Adaptive Neuro-Fuzzy Inference System (Rutkowski *et al.*, 2012)

(i) Knowledge base contains database and rules-base. The prior comprises of membership functions (MFs) of fuzzy sets used in fuzzy rules, while the later contains fuzzy if-then rules.

(ii) Fuzzification converts crisp input variables into a membership degree based on MF defined.

(iii) Inference engine combines fuzzy rules using appropriate fuzzy operator for obtaining accumulated results of fuzzy sets.

(iv) Defuzzification transforms fuzzy output into crisp output value through defuzzification method.

ANFIS is a framework of neuro-fuzzy model that can integrate human expertise as well as adapt itself through learning. It has two types of nodes in this architecture; fixed and adaptable. Nodes of MFs (layer 1) and consequent part (layer 4) are trainable, while nodes for product (layer 2) and normalization (layer 3) are fixed. The network applies least square method to train consequent parameters in forward pass, and uses gradient descent for tuning MF parameters in backward pass of network training. The computational cost of training process depends on the total number of modifiable parameters so Gaussian MF, which uses two parameters (width and center) only, is more preferable than other types of MFs (Awadallah *et al.*, 2009).

Figure 2.4 illustrates ANFIS architecture. For the first order Sugeno model, two fuzzy if-then rules are considered here.

$$Rule1: If\ x\ is\ A_1\ and\ y\ is\ B_1\ then\ f = p_1x + q_1y + r_1$$
$$Rule2: If\ x\ is\ A_2\ and\ y\ is\ B_2\ then\ f = p_2x + q_2y + r_2$$

Or in terms of membership degrees, the above rules can be rewritten as:

$$Rule1: If\ \mu_{A_1}(x)\ and\ \mu_{B_1}(y)\ then\ f = p_1x + q_1y + r_1$$
$$Rule1: If\ \mu_{A_2}(x)\ and\ \mu_{B_2}(y)\ then\ f = p_2x + q_2y + r_2$$

where A_i and B_i are fuzzy sets, or $\mu_{A_i}(x)$ and $\mu_{B_i}(x)$ are MFs in the antecedent, and p_i, q_i and r_i are the consequent parameters that are identified during training process. The five layer architecture of ANFIS shown in Figure 2.4 illustrates the execution of the above two rules.

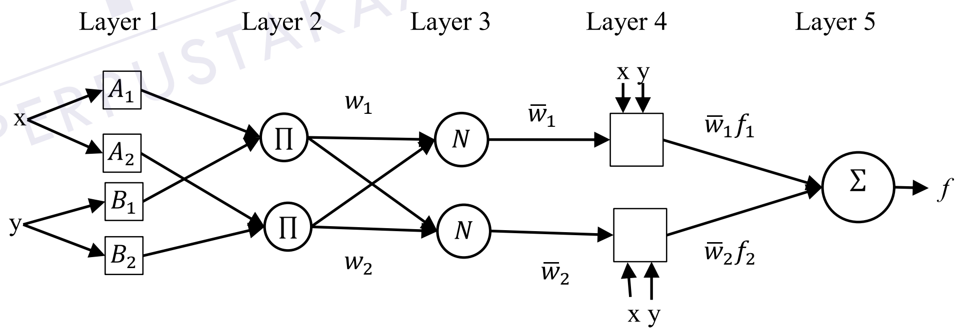

Figure 2.4: ANFIS architecture (Shoorehdeli *et al.*, 2009)

Here, first layer represents inputs, fuzzification is done in second layer, the third and fourth layers represent fuzzy rule evaluation, and defuzzification of the results of the rules is performed in last layer.

Layer 1: Every node i in this layer is an adaptive MF.

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